Artificial Intelligence Impact on Food Security of States in the World

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Abstract. Because food crisis is so wide-reaching, there is a strong a need in the transformation of world agriculture and food production sector. The innovative digital technologies, namely AI, are widely acknowledged as a solution for enhancing food crises management and agricultural productivity. The purpose of this paper is to research the linkage between food security and artificial intelligence against the backdrop of global digitalization processes by using cluster analysis (SOM algorithm). The level of impact of AI on food security is deployed in ascending order for clusters Absence, Starter, Adopter, Frontrunner. Countries with more developed digital infrastructure are better able to respond to current food security threats and build resilience for the future. Due to development of digital economy and AI solutions, the level of food security for clusters of Adopter, Frontrunner is largely higher than for countries with low level of digitalization and AI diffusion (clusters of Absence, Starter). Furthermore, the level of agriculture value added correlates with AI application and country's economic development. The more country's economy depends on agriculture, the lower is country's food security level and the slower is country's digitalization.

Keywords. Artificial intelligence, AI solutions, AgriTech, Agriculture 4.0, Big data, Digital agriculture, Digitalization, Food security, Robotics, SOM algorithm.

1 Introduction

The growing number of world population poses a series of challenges on the current agricultural model, namely the need to increase productivity, reduce costs, and preserve natural resources. The problem is exacerbated by climate change, extreme events are expected to jeopardize agricultural production. At the same time, the frequency and severity of shocks to food systems has increased due to increased number of socio-political (armed conflicts), climatic (extreme weather) and economic events. [1] Even before russia's war against Ukraine disrupted crucial food supply chains, according to Food and Agriculture Organization (FAO) the level of global hunger had reached new records in 2021, with nearly 193 million people in acute food insecurity across 53 territories and in 2022 nearly 258 million people faced food insecurity in 58 countries [2]. The only alternative way to overcome all these challenges is to adopt emerging technologies in agriculture with a particular role of digital component and AI solutions.

According to FAO 'digitalization' of agriculture and the food value chain is ongoing [3] and is already improving access to information, inputs and markets, increasing production and productivity, streamlining supply chains and reducing operational costs. In other words, the world is witnessing the birth of next agricultural technology (agri-tech) revolution that promises to use resources efficiently and achieve food security at local level. According to 2023 WEF Markets of Tomorrow report, 29.7% percent of survey respondents from 126 countries confirmed that agriculture technologies rank first as the top technology of strategic importance globally [4].

The purpose of this paper is to research the linkage between food security and artificial intelligence against the backdrop of global digitalization processes.

We organise the remainder of our paper as follows: in Part 2 we consider related works and summarize the socio-economic impact of AI on food security. Part 3 is devoted to classifying the countries using self-organizing maps and machine-learning techniques into clusters in terms of their food security parameters, digitalization level and economic development. Finally, Part 4 concludes on the results achieved in the research paper.

2 Related Works

2.1 Agriculture 4.0 and AI Solutions Linkage

The technologies, acting in a synergistic and complementary way in agriculture, have the power of transformation that can be referred to as digital agriculture [5], also known as agriculture 4.0 [6], or the fourth agricultural revolution [7]. FAO explains digital agriculture as a process involving digital technologies that covers access, content and capabilities, which, if appropriately combined for the local context and needs within the existing food and agricultural practices, could deliver high agrifood value, and improve socioeconomic, and potentially environmental, impact [8]. Table 1 presents a conceptual comparison between current conventional farming and Agriculture 4.0, based on [5, 9, 10].

Table 1. Comparison between conventional agriculture and Agriculture 4.0

Conventional agriculture (Small-scale farm)	**Agriculture 4.0 (Smart farm)**
Analogical or mechanical Technology	Internet of Things (IoT)
No data or records	Big data
Manual labour	Robotics
Hand or animal power	Automated equipment
Farmer experience	Sensing technologies, satellite image and positioning

According to Silveira, F. D. (Fig.1), there are 3 main levels under the "roof" of Agriculture 4.0 system. *First*, fundamental elements include basic pillars that guide the development of agriculture 4.0 (precision agriculture, smart farming, and digital farming) and without which it could not exist. *Second*, structuring elements cover key technologies that can revolutionize and impact the way commodities are produced, processed, traded, and consumed. *Third*, complementary elements encompass wider possibilities of action of agriculture 4.0. that address specific agricultural issues that require a certain degree of maturity with the structuring elements of agriculture 4.0.

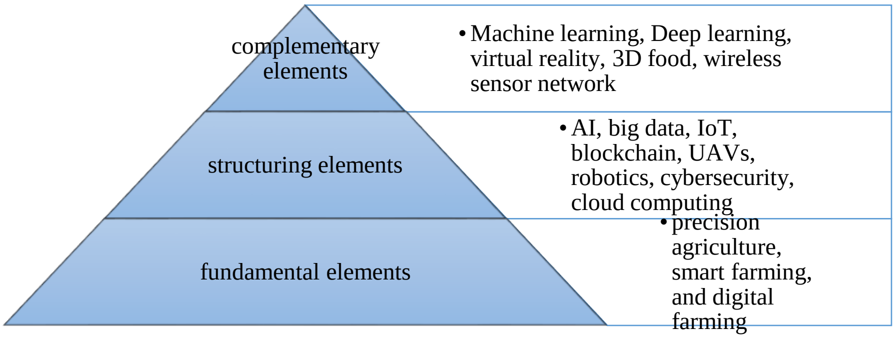

Fig. 1. The "House of Agriculture 4.0" [6]

In terms of digitalization of agriulture, IFAD experts define 6 categories of solutions: 1) advisory and information services; 2) market linkages; 3) supply chain management; 4) financial services; 5) macro-agricultural intelligence; and 6) encompassing integrated solutions [11]. In general, it is expected that technical improvements in new agricultural technologies should: optimize production efficiency (efficient control of machines, cost reduction); optimize quality (timely detection of diseases in crops); minimize environmental impact (efficient use of inputs and pesticides); minimize production-associated risks (more excellent knowledge of cultivated areas, blockchain technology adoption in value chains); build up resilience (ability of food systems to withstand shocks).

AI solutions (purely software or hardware-embedded) have become a mainstream in the global economy for the recent years. In general, AI allows computers and other machines (e.g. robots) to perform tasks previously thought to rely on human experience, creativity and ingenuity. It involves the ability of machines to function autonomously, and "learn" from large volumes of input data, without being explicitly programmed for the required task. [5] The market size of AI application in the global agriculture is expected to grow from USD 1.7 billion in 2023 to USD 4.7 billion in 2028 at CAGR of 23.1% during 2023-2028 period. [12]

Moreover, there is an observable increase in investments in AI start-ups across all industries and in agrifood sector, in particular. According to AgTech report, global investment in foodtech and agtech (agrifoodtech) startups totaled $29.6bn in 2022, a 44% decline on record-breaking 2021 levels ($51.7 billion) [13]. The reasons for such market crush are related to russia's war against Ukraine, inflation, and continued (since COVID-19) supply chain disruptions. But the investment trend remains growing primarily due to the strong returns received by investors from AI capital and strong confidence in AI as a game changer in addressing food security challenges.

2.2 AI Role in Addressing Food Security Challenges

We consulted a number of studies investigating AI role in addressing food security challenges (Table 2).

Table 2. Research on AI solutions in addressing food security

Authors	Research focus
Bhagat P. and al.	proved potential for the application of AI to attain sustainability, especially in predicting the yield, crop protection, climate control, crop genetic control, and produce supply-chain. [14]
Bobicev I., Koeleman E.	importance of AI for dairy farming in developing countries to prove that farmers in Kenya who use local AI platform can increase milk production and significantly improve basic knowledge on insemination time and heat detection [5, p.37]
von Braun J.	broadly based policy agenda to include the poor and marginalized in opportunities of AI/R and to protect them from adverse effects. [15]
How M.L. and al.	unified analysis of data from GFSI to illustrate how computational simulations can be used to produce forecasts of good and bad conditions in food security using multi-variant optimizations providing AI user-friendly approach. [16]
Deléglise H. and al.	models that aim to predict two key indicators of food security: the food consumption score and the household dietary diversity score [17]
Hussain A. et al.	policy recommendations for AI application in agri-food sector, including the need for exploitation and coordinated effort, proper regulation, multi-partner system of estimating AI effects and employment and schooling. [18]

Therefore, we decided to focus our research on investigating whether digitalization, as a whole, and AI solutions, in particular, give countries certain competitive advantages at the macro-level; and how the level of GDP dependence on agriculture correlates with AI application and country's economic development status.

2.3 The Socio-Economic Impact of AI on Food Security

At the times of digital transformation era, the debate over socio-economic impact of applying AI in agriculture and food production (agri-food) sector is ongoing. The main discussion points are briefly summarized at Fig 2.

Fig. 2. Advantages and disadvantages of AI application in agri-food sector

Overall, AI solutions are aimed at increasing farming productivity and crop yield, in particular through predictive analytics-based techniques. Moreover, AI solutions are helpful in soil monitoring, detection of pests and diseases, weather and temperature broadcasting which benefits the entire agri-food supply chain. Thus, these solutions are highly adopted for *first*, enhancing harvest quality in the agriculture industry, *second*, providing support services previously deemed too resource-intensive, expensive, or unavailable (e.g. due to lack of skills and expertise); *third*, driving down current operational costs by saving time and labour performed by agriculture workers. The most widely used AI solutions in agriculture include robotics, big data and sensing techniques (Table 3).

Table 3. Factors affecting the efficiency of most popular AI solutions in agriculture

Factor	Robotics (automation)	Big data (analytics)	Sensing techniques (drones, platforms)
Ownership and management of data	yes	yes	yes
Capacity of end users and data accuracy	yes	yes	yes
ICT infrastructure	yes	yes	yes
Purchase price	yes	yes	yes
Technical maintenance	yes	no	yes
Power asymmetry and dependency	no	yes	no

Elbehri, A. et al., Santos Valle at al. in their works define several factors negatively affecting the efficiency of most common AI solutions, namely, ownership and management of digital data (the absence/ presence of regulations), capacity of end users (technology adaption at the end user) and data accuracy, ICT infrastructure, purchase price, technical maintenance and servicing and power asymmetry and dependency (asymmetry of power between big data service providers and their clients). The first five are inherent to robotics, big data and sensing techniques, whereas power asymmetry and dependency is observed within big data solutions, and technical maintenance problems relate to robotics and sensing techniques.

We can observe that socio-economic impact of AI on food security has dual effect and the main issue is whether the positive effect outweigh the existing negative implications.

3 Main Results: Measuring The Impact of AI on Food Security of States

The main research question of our article is to define the impact of AI technologies on food security of states. *First*, we considered 4 food security parameters of Economist Impact Global Food Security Index (GFSI) 2022 data set. The index covers assessment of food security drivers for 111 countries ranked in GFSI rank 2022 under 4 food security pillars: Affordability, Availability, Quality and safety, Sustainability and adaptation. As of today, GFSI remains the major benchmarking model in terms of food security assessment, including 68 qualitative and quantitative food security drivers (Table 4).

Table 4. GFSI 2022 food security drivers

Affordability	Availability	Quality and Safety	Sustainability and adaptation
1.Change in average food costs FAO Consumer Production Index 2.Proportion of population under global poverty line 3.Inequality-adjusted income index 4.Agricultural trade 5.Food safety net programmes	1.Access to agricultural inputs 2.Agricultural research & development 3.Farm infrastructure 4.Volatility of agricultural production (FAO) 5. Food loss (FAO) 6. Supply chain infrastructure 7. Sufficiency of supply 8. Political and social barriers to access 9.Food security and access policy commitments	1.Dietary diversity 2.Nutritional standards 3.Micronutrient availability 4.Protein quality 5.Food safety	1.Exposure 2.Water 3.Land 4.Oceans, rivers and lakes 5.Political commitment to adaptation 6.Disaster risk management

Second, to account the impact of digitalization level (i.e. digital economy development, including AI solutions), we decide to choose the Global Connectivity Index (GCI) that evaluates the progress of 70 economies in deploying digital infrastructure and capabilities. GCI defines 3 categories of countries — Starter, Adopter, and Frontrunner and we will try to attribute this classification to the results of our analysis.

Third, in our research we included Agriculture value added (% of GDP) parameter that reflects the importance of agriculture sector development in country’s GDP [19]. It also serves as a marker for country’s level of economic development.

To sum up, to research the impact of AI on food security level we will build country clusters [20, 21, 22] to take into account 4 GFSI dimensions, GCI and Agriculture value added via unsupervised self-organizing maps with input layer of 6 neurons. All countries are self-organizing on the output layer neurons. The average distance to the nearest neurons after 100 iterations is decreased on almost third (Fig. 3).

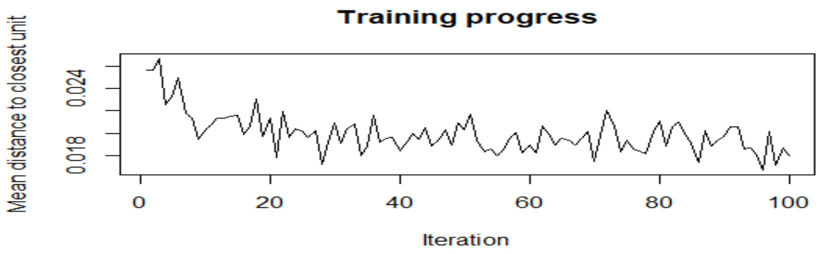

Fig. 3. Decrease in average distance to the nearest neurons after 100 learning iterations of the SOM network

The codes plot displays the value of 6 factors for each node, which corresponds to 111 countries. For the number of clusters k=6, we have performed hierarchical clustering through SOM algorithm and have constructed the maps of the codes type. The results obtained are presented at Fig. 4.

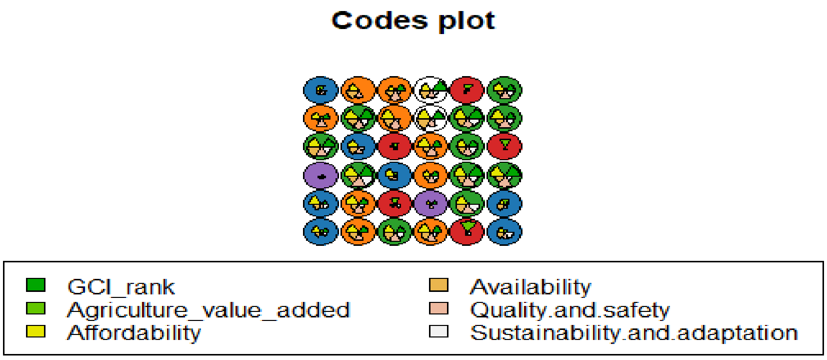

Fig. 4. Clustering of SOM map nodes

As a result of the analysis, we defined 6 country clusters as represented in Table 5 and classified them under 3 GCI categories (plus adding Absence category).

Table 5. Clusters by countries

Clusters	Countries	GCI category
Cluster 1 (C1 - blue)	29 countries: Algeria, Azerbaijan, Bangladesh, Burkina Faso, Cambodia, Dominican Rep., Egypt, Ghana, Guatemala, Honduras, India, Indonesia, Jordan, Kenya, Laos, Myanmar, Nepal, Nicaragua, Pakistan, Panama, Philippines, Rwanda, Senegal, Sri Lanka, Tajikistan, Tanzania, Thailand, Tunisia, Uzbekistan	*Starter*
Cluster 2 (C2-orange)	28 countries: Argentina, Bahrain, Bolivia, Brazil, Bulgaria, Colombia, Ecuador, El Salvador, Greece, Hungary, Israel, Italy, Kuwait, Malaysia, Mexico, Morocco, Oman, Paraguay,	*Adopter*

	Qatar, Romania, Saudi Arabia, Serbia, Slovakia, South Africa, Turkey, Ukraine, United Arab Emirates, Vietnam	
Cluster 3 (C3 - green)	26 countries: Australia, Austria, Belgium, Canada, Chile, Costa Rica, Czech Republic, Denmark, Finland, France, Germany, Ireland, Japan, Kazakhstan, Netherlands, New Zealand, Norway, Peru, Poland, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States, Uruguay	*Frontrunner*
Cluster 4 (C4 - red)	20 countries: Benin, Burundi, Cameroon, Chad, Congo (Dem. Rep.), Côte d'Ivoire, Ethiopia, Guinea, Haiti, Madagascar, Malawi, Mali, Mozambique, Niger, Nigeria, Sierra Leone, Syria, Togo, Uganda, Yemen	*Absence*
Cluster 5 (C5 - purple)	5 countries: Angola, Botswana, Sudan, Venezuela, Zambia	*Absence*
Cluster 6 (C6 - white)	3 countries: China, Singapore, South Korea	*Frontrunner*

The sets of attributes of each country cluster are illustrated in Fig. 5.

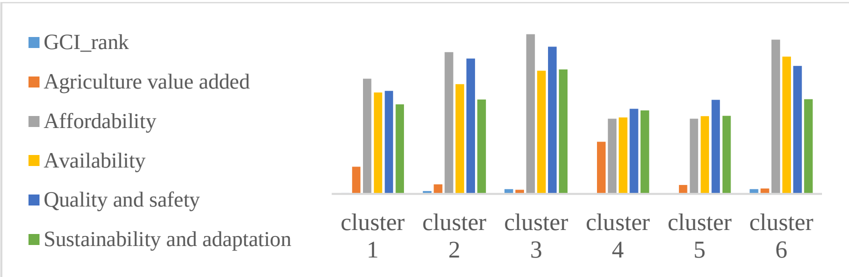

Fig. 5. Clusters by attributes

As regards comparative advantages, food is most affordable and available in C3 and C6, the lowest affordable – in C4 and C5. The highest quality and sustainability is observed in C3, the very low quality food is in C4. The comparative advantages of each cluster are presented in Table 6.

Table 6. Clusters comparative advantages

<table>
<tr><th>Comparative advantages</th><th>Very high</th><th>Above average</th><th>Below average</th><th>Very low</th></tr>
<tr><td>Affordable food</td><td>C3, C6</td><td>C2</td><td>C1</td><td>C4, C5</td></tr>
<tr><td>Quality food</td><td>C3</td><td>C2, C6</td><td>C1, C5</td><td>C4</td></tr>
<tr><td>Digital development and AI</td><td>C3, C6</td><td>C2</td><td>x</td><td>C1, C4, C5</td></tr>
<tr><td rowspan="2">Available food</td><td>C6</td><td>C3</td><td>C4</td><td>C5</td></tr>
<tr><td></td><td colspan="2">C1, C2</td><td></td></tr>
<tr><td rowspan="2">Sustainable food</td><td>C3</td><td></td><td>C1, C4, C5</td><td>x</td></tr>
<tr><td></td><td colspan="2">C2, C6</td><td></td></tr>
</table>

Agriculture value added	C4	C1	C2, C5	C3, C6

From the standpoint of our research the competitive advantages of digital technologies are the most interesting. Taking into account dependence between pillars of GFSI and GCI rank (level of digital development and AI) we can conclude that the more GFSI the more GCI rank (C2, C3, C6) and vice versa: the less GFSI the less GCI rank (C1, C4, C5). If we consider dependence between GFSI rank and Agriculture value added, we see that the more important is agriculture for country's economy, the less digitally developed it is and the more food insecure (C1, C4, C5) and vice versa: the more GFSI the less Agriculture value added (C2, C3, C6) and the more digitalised is the country.

The GCI categories were further used to perform the analysis of GFSI rank and agriculture value added for deferent level of AI development (Fig. 6) to prove AI comparative advantages. The countries with higher GCI rank (factor 3) have greater digital readiness and resilience, than countries with factor 1, thanks to strong digital infrastructure and as a result the potential of AI application. We can also observe that the greater the level of implementation of AI in a country, the higher the level of food security of the respective countries.

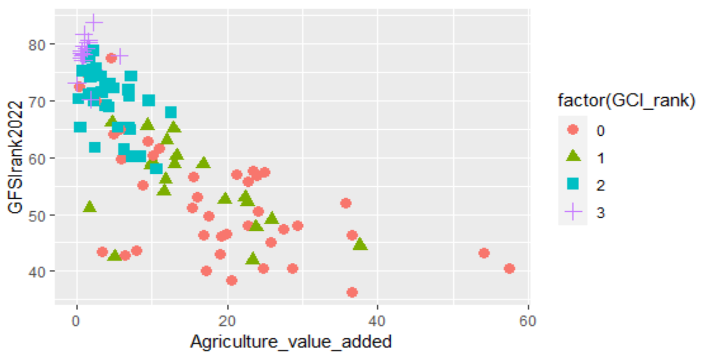

Fig. 6. GFSI rank and agriculture value added for deferent level of AI development

To check the validity of obtained results, we used the list prepared by Yahoo of 12 most advanced countries in agriculture technology (by number of agritech startups) [23]. And the results of our modelling confirm that the countries that have the biggest number of tech startups are situated in C3 and C6 with the lowest level of GDP dependency on agriculture and the highest food security level. These countries are (Australia (3), Canada (3), China (6), France (3), Germany (3), Israel (6), Japan (3), Netherlands (3), New Zealand (3), South Korea (6), UK (3), United States(3)). The majority of countries with developed agri-tech sector have two things in common – advanced economy status and high agricultural output. The latter has compelled these countries to invest in innovation in agri-technology to sustain and grow their outputs.

The regional scope of the obtained results is presented at Fig. 7. We start from defining C3, C6 as Industrial, Post-industrial economics with low level of agriculture value added in GDP, whereas other countries shall be regarded as Agrarian economies.

The results obtained on countries in C1, C4 and C5 highly correlate with the 2023 FAO distribution of 45 countries in need of external assistance of food [24], therefore we shall call these clusters as Agrarian economies in Emergency.

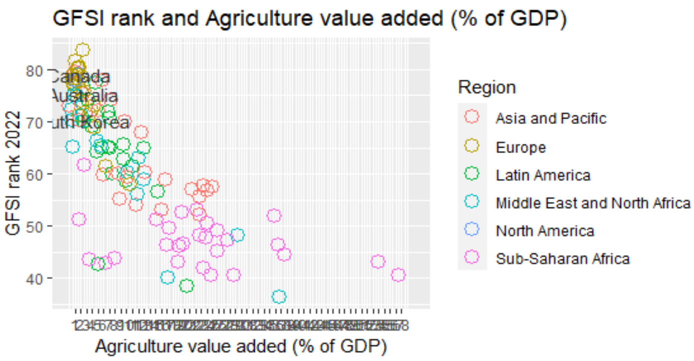

Fig. 7. Trade-offs between GFSI rank and agriculture value added by regions

Multiple regression between GFSI rank as dependent variable and explanatory variables (GCI rank and Agriculture value added) demonstrates that movement in clusters' countires from Absence to Starter, from Starter to Adopter, from Adopter to Frontrunner give rise to GFSI rank by an average of 5.6 positions. The more country's economy depends on agriculture, the lower the country's food security rating GFSI. If a country's agricultural value added increases by 1%, the country's GCI rating will decrease by 0.5 positions on average (Fig. 8).

```
lm(formula = GFSIrank2022 ~ GCI_rank + Agriculture_value_added,
    data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-21.2285  -3.8918   0.9052   3.7857  18.9536

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             60.69808    1.67014  36.343  < 2e-16 ***
GCI_rank                 5.63230    0.72103   7.811 3.94e-12 ***
Agriculture_value_added -0.50038    0.07135  -7.013 2.13e-10 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.652 on 108 degrees of freedom
Multiple R-squared:  0.7331,    Adjusted R-squared:  0.7281
F-statistic: 148.3 on 2 and 108 DF,  p-value: < 2.2e-16
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Fig. 8. Multiple regression model of GFSI rank

Therefore, countries with more developed digital infrastructure are better able to respond to current food security threats, and build resilience for the future.

4 Conclusions

To sum up, we conclude that the transformative power of digital technologies, in general, and AI solutions, in particular, give countries certain competitive advantages to withstand current food security crisis. First, we found that the rise of GCI rank (level of digital development and AI) can increase food security index (GFSI rank) by an average of 5.6 positions. Therefore, due to development of digital economy and AI, the level of food security for clusters of Adopter, Frontrunner is largely higher than for countries with low level of digitalization and AI diffusion (clusters of Absence, Starter). Second, we found that if a country's agricultural value added increases by 1%, the country's GCI rating will decrease by 0.5 positions on average. This proves that the level of GDP dependence on agriculture correlates with AI application and country’s status of economic development (Post-industrial, Industrial, Agrarian economies; Agrarian economies in Emergency).

We are going to further continue our research, specifically, in terms of assessing the modern instruments (namely, AI) of achieving food security in already precarious state and constant threats.

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